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CLASS ASSOCIATION RULE MINING FOR ANALYZING DEFORESTATION FACTORS

K.SARITHA[1], S. JYOTHI[2] & K. R. MANJULA[3]

[1]Research Scholar, Department of Computer Science, Sri Padmavati Women's University, Tirupati, Andhra Pradesh, India

[2]Professor, Department of Computer Science, Sri Padmavati Women's University, Tirupati, Andhra Pradesh, India

[3]Asst. Professor, Department of CSE, SASTRA University, Thanjavur, Tamilnadu, India

ABSTRACT

Deforestation is an important emerging factor in the developing countries, this leads to permanent clearing of forests which is having major impact on finite resources.Monitoring of forest destruction has to be done with the change of time analysis and is necessary to drive the factors of deforestation.It is essential to identify and understand the causes of deforestation.

Drivers of deforestation can be categorized in different ways like urbanization, agriculture, roads, and mining. Categorization can be done by using classification technique in data mining.We analyzed forest cover maps based on satellite data, converted to geospatial database to obtain the output. The objective of this paper is to focus on the factors of deforestation and their associations in the study area. This paper presents the class association rules for deforestation data set which yields high accuracy than general classification and association rules.

KEYWORDS: Deforestation, Data Mining, Association Rule, Class Association Rule, Classification

INTRODUCTION

Due to the increasing volume and complexity of databases, the search for new techniques of data mining has been emphasized [9].Data Mining or Knowledge Discovery is needed to make sense and use of data. Knowledge Discovery in Data is thenon-trivial process of identifying valid, novel, potentially useful and ultimately understandable patterns in data [7].Data mining is defined as an information extraction activity whose objective is to discover hidden facts contained in databases.Data mining tasks including association rules mining, classification and prediction, as well as cluster analysis have been successfully utilized in analyzing spatial data related to forest fires [11][16][17][6][23][12].

Generally speaking, association rule mining [3] and classification rule mining [21] are most effective and efficient techniques in data mining. Association rule mining was originally intended to discover regularities between items in large transaction databases [1].Classification rule mining is widely used in predicting class of future objects whose class label is not known. Even though there is a lot of difference between association and classification techniques, both association rules and classification rules can be represented as if-then type rules

To discover strongly correlated rules, different measures have been proposed to evaluate the interestingness of patterns, such as support and confidence[3]. Association rule mining is one of the techniques that use the concept of support and confidence to identify the interesting rules. The use of association rule mining in classification rule was first introduced in 1997 byAli et. al, Bayard[4][2] and it was named as class association rule or associative classification. The first classifier based on association rules was CBA [18] given by Liu et al. in 1998.

Class association rule mining process can be categorized in three steps:

- Finding frequent item sets and frequent class association rules.

- Then find the strong class association rules by pruning the weak rules.
- Design a classifier [21].

In the recent trends deforestation is one of the most potent factors for degradation of ecosystem. Differentiation between natural and human induced forest changes is a complex task, but must be analyze the underlying causes of disturbances in forest change. This can be done by embedding Remote sensing and Geographical Information System(GIS). Research using remotely sensed satellite data has attracted attention on image classification, because classification results are basis for interpretation, analysis and modeling for various environmental and socio-economic applications [13].Remote sensing is a set of activities to obtain information from objects that constitute the Earth's surface, regardless physical contact with them, using satellites [23]. Data mining techniques can be applied for generating the class association rules for analyzing the deforestation. In this paper we applied classification association rule technique for our data to analyze the classes and association among them. We simulated the class association rules in WEKA data mining tool, an open source suite of machine learning algorithms.

PROBLEM DOMAIN

Forests are a critical component of the planet's ecosystem. Unfortunately, there has been significant degradation in forest cover over recent decades as a result of logging, conversion to crop, mining and urbanization or disasters (natural or man-made) such as forest fires, floods, and hurricanes [19]. Substantial attention is being given to the sustainable use of forests. A key to effective forest management is to play attention to acquire knowledge about changes in forest and identifying the factors of declining forest area.This can be done through integration of GIS, RS and data mining techniques.The study area covers the 5000 square kilometers which includes Chittoor, Kadapa and Nellore districts. The boundary lies between lower left East 78° 45" Longitude and E 13°35" Latitude and the upper right corner N 79° 39" Longitude and N 14°33" Latitude with an area of 15,379 square kilometers of Kadapa district, which includes 51 Mandals and three Revenue Divisions. The geographical area of Chittoor district lies between 12°37"to 14°18" N Latitude and 78° 33"to 79°55" E Longitude. The district area is 13,076 square kilometers divided into three Revenue Divisions and 46 Mandals administratively. The data is derived from the Manjula et.al (2011) consisting of maps and tables regarding the association technique[20]. The data set consists of 5 attributes and 99 instances. The study area outline map of the district is specified in Figure 1:

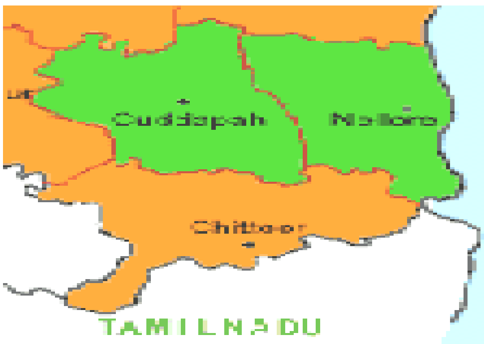
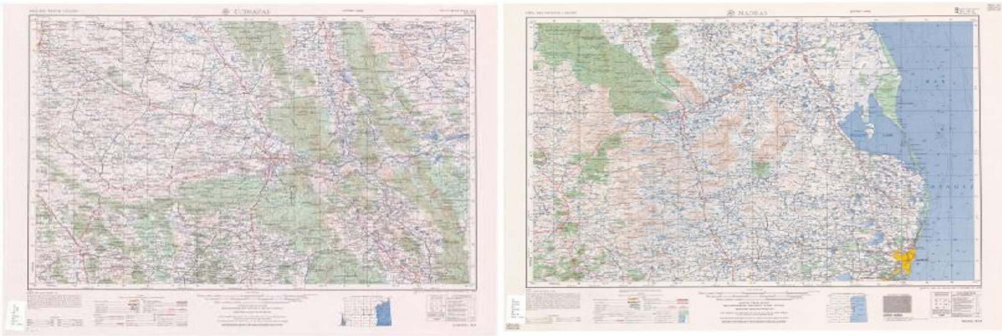


Figure 1: Outline Map of Study Area

Data Preprocessing

We have collected 1991, 2001 and 2011 images, from that images we explore the digital data using image analysis [20]. The figures 3(a) and (b), 2.2 (a), (b) and (c) denotes toposheets, satellite images of the study area.



(a) (b)

Figure 2: Maps Showing the Topography and Study Area of Forest

(a) (b) (c)

Figure 3: Study Reference Map:(a) Row Index Map of AP (b) Boundary Map (c) SIGHT of Study Area

Data Preparation

Comparing the results of classified images is the best approach for detecting the change in satellite images. The comparison of classified-map not only identifies the location but it also shows the nature and change type are determined for the study area. Our Primary objective is to define the deforestation by considering only two classes forest and non-forest. Figure2.2, 2.3 shows the toposheets, thematic and scanned images by which the base map is generated. Figure2.4 is a base map which displays the details of mandals of study area. Then using the approach of ISO Cluster and Maximum-Likelihood method we classified the three images which represents three decades. By deriving the classification results, the maps are generated as outputs.

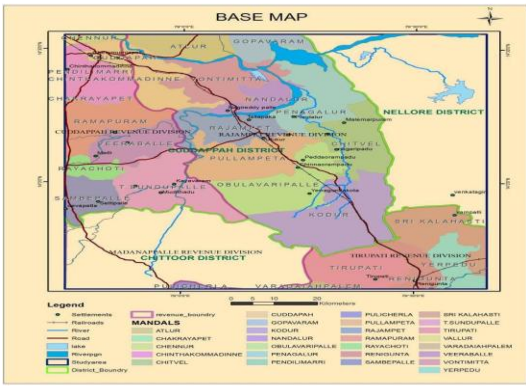


Figure 4: Outline Map Showing Mandals of Study Area

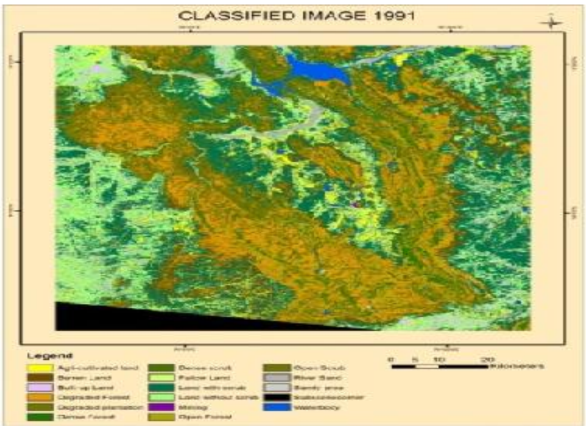


Figure 5: Classified Raster Image

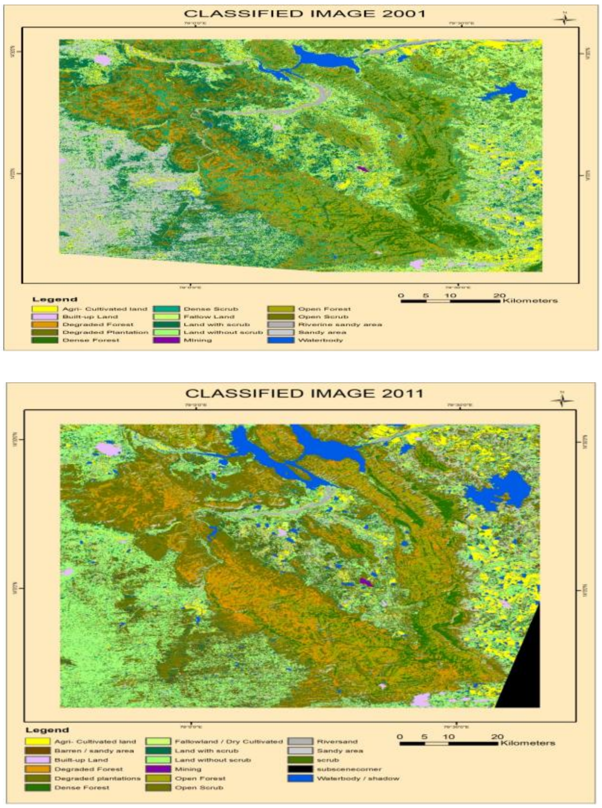


Figure 6: Study Area Classified Vector Images of 1991 2001 and 2011

Table 1: Spatial Predicate for the Year 1991(Singlemine1991)

OID	Name	Location_Type	District_Name	Agriculture-Cultivated	Built-up	Mining	Degradation	Adjacent to Degraded	Road Buffer-Intersect
	Atlur	Mandal	Cuddapah	2	6	1	1035	26	
	Chakrayapet	Mandal	Cuddapah				11		
	Chennur	Mandal	Cuddapah	4			41		37
	Chinthakommadinne	Mandal	Cuddapah	2			1011		72
	Chitvel	Mandal	Cuddapah	78			2562		
	Gopavaram	Mandal	Cuddapah				1264		
	Kadapa	Mandal	Cuddapah	18			1852		755
	Kodur	Mandal	Cuddapah	171	1		4956		1499
	Cuddapah	District	Cuddapah	2029	6		45846		
	Nandalur	Mandal	Cuddapah	31			415		178
	Obulavaripalle	Mandal	Cuddapah	115		3	2763		317
	Penagalur	Mandal	Cuddapah	83			3416		19
	Pullampeta	Mandal	Cuddapah	96			2248		
	Rajampet	Mandal	Cuddapah	95			975		371
	Ramapuram	Mandal	Cuddapah	12			1126		
	Renigunta	Mandal	Chittoor	23			527		890
	Sambepalle	Mandal	Cuddapah	6			21		
	Srikalahasti	Mandal	Chittoor	29			1261		123
	T Sundupalle	Mandal	Cuddapah	65			1390		
1	Tirupati	Mandal	Chittoor	49	3		2327		461
	Varadaiah Palem	Mandal	Nellore	4			17		
	Veeraballe	Mandal	Cuddapah	20			1056		
	Vontimitta	Mandal	Cuddapah	20			1056		331
	Yerpedu	Mandal	Chittoor	53			525		43

Table 2: Spatial Predicate for the Year20011(Singlemine2001)

OID	Name	Location_ Type	District_ Name	Agriculture-Cultivated	Built-up	Mining	Adjacent to Degraded	Road Buffer-Intersect	Within Road
	Atlur	Mandal	Cuddapah	26			2969		
	Chennur	Mandal	Cuddapah	15			133	1	
	Chinthakc	Mandal	Cuddapah	56			2206	141	
	Gopavarai	Mandal	Cuddapah	6			3509		
	Kadapa	Mandal	Cuddapah	65			4125	2002	
	Kodur	Mandal	Cuddapah	159		2	6023	2090	
	Cuddapah	District	Cuddapah	1715	3	1	84349	8867	8708
	Nandalur	Mandal	Cuddapah	5	1		871	371	
	Obulavari	Mandal	Cuddapah	87		4	5676	325	
	Penagalur	Mandal	Cuddapah	48			6556		
	Pullampet	Mandal	Cuddapah	115			4190	456	
	Rajampet	Mandal	Cuddapah	63			1703	349	
	Ramapura	Mandal	Cuddapah	11			2647		
	Rayachoti	Mandal	Cuddapah				7		
	Renigunta	Mandal	Chittoor	25			716	710	
	Sambepal	Mandal	Cuddapah				18		
	Srikalahas	Mandal	Chittoor	64			1284	37	
	T Sundupa	Mandal	Cuddapah	15			3069		
1	Tirupati	Mandal	Chittoor	102	1		5494	1156	
	Vallur	Mandal	Cuddapah	3			6	1	
	Varadaiah	Mandal	Nellore	47			289		
	Veeraball	Mandal	Cuddapah	10			1553		
	Yerpedu	Mandal	Chittoor	81			788	58	

Table.3: Spatial Predicate for the Year2011 (Singlemine2011)

OID	Name	Location_Type	District_Name	Agriculture-Cultivated	Built-up	Mining	Adjacent to Degraded	Road Buffer-Intersect	Within Road
	Atlur	Mandal	Cuddapah	26			2969		
	Chennur	Mandal	Cuddapah	15			133	1	
	Chinthakommadinne	Mandal	Cuddapah	56			2206	141	
	Gopavaram	Mandal	Cuddapah	6			3509		
	Kadapa	Mandal	Cuddapah	65			4125	2002	
	Kodur	Mandal	Cuddapah	159		2	6023	2090	
	Cuddapah	District	Cuddapah	1715	3	1	84349	8867	8708
	Nandalur	Mandal	Cuddapah	5	1		871	371	
	Obulavaripalle	Mandal	Cuddapah	87		4	5676	325	
	Penagalur	Mandal	Cuddapah	48			6556		
	Pullampeta	Mandal	Cuddapah	115			4190	456	
	Rajampet	Mandal	Cuddapah	63			1703	349	
	Ramapuram	Mandal	Cuddapah	11			2647		
	Rayachoti	Mandal	Cuddapah				7		
	Renigunta	Mandal	Chittoor	25			716	710	
	Sambepalle	Mandal	Cuddapah				18		
	Srikalahasti	Mandal	Chittoor	64			1284	37	
	T Sundupalle	Mandal	Cuddapah	15			3069		
1	Tirupati	Mandal	Chittoor	102	1		5494	1156	
	Vallur	Mandal	Cuddapah	3			6	1	
	Varadaiah Palem	Mandal	Nellore	47			289		
	Veeraballe	Mandal	Cuddapah	10			1553		
	Yerpedu	Mandal	Chittoor	81			788	58	

Tables 1, 2 and 3 gives the spatial predicates that are derived from the output of classified images to set as input for generating classification rules.

CLASS ASSOCIATION RULE MINING

Association Rule Mining

Association Rule Mining is one of the vital approaches in data mining for finding frequent item sets. Association rules are capable of revealing all interesting relationships in large databases. An association rule is defined as "Let I = $\{i_1, i_2, \ldots . i_m\}$ be a set of literals, called items. LetD be a set of transactions (database), where each transaction.T is a set of items such that $T \subseteq I$. TID indicates a uniquetransaction identifier. An association rule is an implicationof the form $X \rightarrow Y$, $X \subseteq I$ and $Y \subseteq I$ and $X \cap Y = \Phi$. X iscalled antecedent while Y is called the consequence of therule."This method is well

known in data mining and is applied to market analysis by looking for items that arefrequently associated in a commercial transaction [7]. It has been extended to deal with spatial data to expressrules like:

A_1^A_2...^A_m^Spatial Relations => B_1^...^B_n^ Spatial Relations [s, c],where A_i and B_j arepredicates like attribute=constant_value , s is the rule support and c the rule confidence. These rules are usedto find associations between properties of objects and those of neighboring objects. The rules that satisfy both minimum support and confidence threshold are said to be strong association rules.

For example, the rule : is_a (x, gas_station) ^ within (x, rural_area) -> close_to (x, highway) [65%, 80%] [4]

CLASSIFICATIONS

Classification is one of the important areas of data mining[9].Classification is a data mining technique where the data stored ina database is analyzed in order to find rules that describe the partition of the database into a given set of classes. Each object in a database is assumed to belong to a predefined class, as it is determined by one of the attributes, called the class label attribute. A number of classification methods were proposed by statistics and machine learning researchers[7]. The objective of classification is to predict the class of future objects whose class label is not known.

Association rules and classification rules are represented as *ifthen*type rules. However, there are some dissimilarityamong them. Association rules are commonly used asdescriptive tools, which provide the association relationships tothe specific application experts, whereas classification rulesare used for predicting the unseen testing data. However, amajor problem in association rule mining is its complexity.The result of an association rule mining algorithmis not the set of all potential relationships, but the set of allinteresting ones. That is an vital issue of the miningprocess, but the quality of the resulting rule set is ignored.On the other hand there are approaches to explore thediscriminating power of association rules and use themaccording to this to solve a classification problem [26][5].

Class Association Rule Mining

Associative classification is a recent and novel technique that applies the method of association into classification and achieves high classification accuracy. Let Dbe a dataset with *T*set of tuples. Each tuple follows the schema (A_1,A_2, . . .,A_N,A_C),in which (A_1,A_2, . . . , A_N) are N attributes and$A_C$is the target class. The attributes may be either categorical or continuous.For continuous attributes, the value range is discretized into intervals. An attribute-value pair is represented as an *item*. For any two disjoint frequentattribute-value subsets X and Y of A, the patterns of the form $X \rightarrow Y$ are called association rules, where X and $Y$are disjoint sets (ie., $X \cap Y = \emptyset$). Frequent attribute-value sets and then association rules can be generated using the popularmethods Apriori[3][8], FP-Growth[10][8] or any other well-known techniques. The attribute-value sets X and $Y$are called antecedent and consequent of the association rule respectively. Class Association Rules (CARs) are the association rules with class label attribute as the only consequent. Let **A**={A_1,A_2,A_3,…,A_m,C} be the m+1 distinct attributes and **C**={c1,c2,…,ct} be the class label attribute with t number of classes. Supposeitem set $T \subseteq A$, A is the item set of any items with attributes (A_1,A_2, . . .,A_N),c is 1-itemset of class attribute, a class association rule can be represented as

$$T \Rightarrow c$$

Here, Tmay contain a single item or multiple items.

CAR rule is of the form **L**→ (C,ci), where the pattern **L** is the attribute-value pair from the attribute set {**A** \ **C**} and ci is the class label value for **C**[KB10]. Generation of class association rules (CARs) is generally controlled by the two measurescalled support and confidence, which are given below:

Support = $P(X \cup Y) = P(XY)$ = (Number of tuples that contains both X and Y) / (Total number of tuples in **D**)

Confidence = $P(Y \mid X) = P(X \cup Y) / P(X) = P(XY) / P(X)$

The first algorithm that bring an idea of using an association for classification was the CBA algorithm proposed by Liu et.al[18]. The CBA algorithm is

*F*1 = {large 1-ruleitems};

*CAR*1 = genRules(*F*1);

*prCAR*1 = pruneRules(*CAR*1);

for (*k* = 2; *Fk*-1≠ ϕ _ ; *k*++) **do**

Ck = candidateGen(*Fk*-1);

for each data case *d*

–

D **do**

Cd = ruleSubset(*Ck*, *d*);

for each candidate *c*∈*Cd* **do**

c.condsupCount++;

if *d*.class = *c*.class **then** *c*.rulesupCount++

end

end

Fk = {*c*∈*Ck* | *c*.rulesupCount≥*minsup*};

CARk = genRules(*Fk*);

prCARk = pruneRules(*CARk*);

end

CARs = ∪*k* *CARk*;

prCARs =∪_*k* *prCARk*;

Figure 7: The CBA-RG Algorithm

The function of above algorithm is as follows: In the first pass of the algorithm, it counts the item and class occurrences to determine the frequent 1-ruleitems, from this, a set of CARs is generated by gen Rules. Pruning is also done in each subsequent pass to CAR_k. Pruning a rule is as follows: If rule r's pessimistic error rate is higher than the pessimistic error rate of rule r, then rule is pruned.

For each successive pass, say k*th* pass, the algorithm performs 4 major tasks. First, the frequent rule *Fk*-1 found in the (*k*-1)*th* pass are used to generate the candidate *rule Ck* using the *condidateGen* function(line 5). It then scans the database and updates differentsupport counts of the candidates in *Ck* . Afterthose new frequent*rules* have been identified to form*Fk* , the algorithm then produces the rules *CARk*using the *genRules* function. Lastly, rule pruningis performed on these rules.

The candidategen work is similar to the function Apriori algorithm. The main variance is here it need to increment the support counts of the condset and the rule separately, but in Apriori algorithm only one count is updated. The original set of rules is in CARs and pruned rules will be in prCARs.

Mining class association rules can be viewed as a special form of mining association rules, since a set of association rules with predefined objectives can be used for classification. The class association rule approach consists of two steps: (1) First it implements the famous Apriori algorithm in order to discover frequent item sets. (2) Second step involves in building the classifier.

In the first phase, *rule generation*, *CAR* computes the *complete* set of rules in the form of R:T→c where is a pattern in the data set, and cis a class lab,el such that sup{R}and conf{R}pass the given support and confidence thresholds, respectively. Furthermore, *CAR* prunes rules and only selects a subset of high quality rules for classification.

In the second phase, *classification*, *CAR* extracts a subset of rules matching the itemand predicts the class label of the item by analyzing this subset of rules.

In this paper our analysis is focused on applying the class association rules for our data set.

EXPERIMENTS AND RESULTS

From the above Remote Sensing data and tables we are extracted the data for year 1991, 2001 and 2011 and developed the deforestation data set for the study area. The sample deforestation data set whichis converted in to arff file is given Table 4.

WEKA is the popular data mining system developed at the University of Waikato. It is an open source machine learning environment which consists of useful data mining and machine learning algorithms. In this paper, we implemented the association rule-based classification in the WEKA framework. We used our dataset which is given in the below Table, it is a sample dataset given which depicts the information about different possibilities of deforestation factors of the original dataset.

Table 4: Sample Arff Data Set

No.	Agri Nominal	Built-up Nominal	Mining Nominal	Road Nominal	Class Nominal
1	yes	yes	yes	no	ABM
2	yes	no	no	yes	AR
3	yes	no	no	yes	AR
4	no	no	no	yes	R
5	yes	no	no	yes	AR
6	yes	yes	yes	yes	ABMR
7	yes	yes	yes	no	ABM
8	yes	no	no	yes	AR
9	yes	no	yes	yes	AMR
10	yes	no	yes	yes	AMR
11	yes	no	no	no	A
12	yes	no	no	yes	AR
13	yes	no	no	yes	AR
14	yes	no	no	yes	AR
15	yes	no	no	yes	AR

Class association rule mining can be done through WEKA machine learning language with the Apriori algorithm which is an association rule mining technique in data mining which has an option of car in WEKA. If the option car is enabled to true then classification rules are mined as a substitute of common association rules. We define it by the class index which is the class attribute. If the class index is set to -1 the last attribute in the data set is taken as class attribute, then we get the same consequence of association rules forming class association rules. This method is applied for our data set to retrieve the class association rules and we acquired the some of the interesting rules.

Some interesting Class Association Rules are:

1. Agri=yes Built-up=no Mining=no Road=yes 42

==> Class=AR 42 conf:(1)

2. Agri=yes Mining=yes Road=yes 17 ==>

Class=AMR 17 conf:(1)

3. Built-up=yes Road=no 12 ==> Class=B 12

conf:(1)

4. Agri=yes Built-up=yes Road=no 12 ==>

Class=AB 12 conf:(1)

5.Agri=no Mining=yes Road=yes 12 ==>

Class=BM 12 conf:(1)

6. Built-up=yes Mining=yes Road=yes 12 ==>

Class=BMR 12 conf:(1)

7. Agri=yes Built-up=yes Mining=yes Road=yes 12

==> Class=ABMR 12 conf:(1)

8. Agri=noBuilt-up=no Road=yes 11 ==> Class=R

11 conf:(1)

9. Agri=yes Built-up=yes Road=yes 11 ==>

Class=ABR 11 conf:(1)

10. Agri=yes Mining=no Road=no 11 ==> Class=A

11 conf:(1)

12. Built-up=yes Mining=no Road=yes 11 ==>

Class=BR 11 conf:(1)

13. Agri=yes Built-up=no Mining=no Road=no 11

==> Class=A 11 conf:(1)

Let us Consider the some of the Rules

Rule1

This rule represents even built-up and mining is not forest agriculture development leads to roads construction then agriculture and roads are the factors of degradation of forest.

Rule 12

Represents that sometimes roads are not constructed even agriculture is developed in the forest in such cases only agriculture is the factor for deforestation.

Rule 7

This rule shows if the development of built –up area may leads to construction of roads there by the built-up and roads are considered as the factors of deforestation. In some cases even the urbanization that is built-up area is developed the roads are not constructed it is clearly shown in rule 3.

Rule 8

According to this rule, we noticed that there is no extension of agriculture land and built-up area but the extension of roads may occur which leads of degradation of forest and the factor of deforestation is identified as road.

CONCLUSIONS

There are several individual methods are there for achieving classification and association rules. But combining the classification and association technique is the novel methodology which applies association into classification technique and also yields high accuracy of classification rules. The main objective of this paper is to the class association rules for our data set. The experiment is done on our data set to achieve the validate results. We examined two major challenges in class association rules: Efficiency in handling large number of association rules and effectiveness in predicting new class labels with greater accuracy.

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AUTHORS DETAILS

K. Saritha[1] received M.Sc(Computer Science) degree from Sri Krishadevaraya University, Anantapur in 1999 and M.Phil degree in Data mining in 2005 from Sri Padmavathi Mahila University, Tirupati, currently pursuing the Ph.D degree in Compter Science in the field of Datamining . She is currently working as Assistant Professor in KSRM College of Computer Studies, Kadapa with 12 years of experience. She has published papers in journals, presented papers in conferences and attended workshops. She has guided more than 30 PG projects.

S. Jyothi[2] is working as Professor & BOS Chairperson in the Department of Computer Science, Sri Padmavathi Mahila Visvavidyalayam(SPMVV), Tirupati. She is also Director of University Computer Centre. **Educational Qualifications:** M.Sc in Applied Mathematics from S.V.University, Tirupati , M.S in Software Systems from BITS, Pilani, & Ph.D in Theoritical Computer Science from S.V.University, Tirupati. She is life member of ISTE & CSI, member of IEEE and professional member ACM. **Teaching & Research Experience:** 22 years teaching experience & 23 years research experience (guided 7 Ph.D. and 6 M.Phil. scholars). **Current Research Interests:** Fuzzy Systems, Neural Networks, Data Mining, Pattern Recognition and Image processing.She is member ofISTE and CSI and IEEE.

K.R. Manjula[3]received Ph.D from Sri Padmavati Mahila University, Tirupati in 2012. She has 20 years teaching experience and presently she is working as a Senior Assistant Professor in Dept of CSE, Sastra University, Thanjavur, Tamilnadu. She published and presented more than 10 research papers. She has guided more than 40 PG projects.